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A Novel Machine Learning Approach for Classifying Resting EEG Data to Detect Possible Propensities for Executive Dysfunction

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Abstract
Executive dysfunction defines the lack of ability to plan, sequence, or temporally structure behavior, which is essential in daily life and thus drastically reduces the quality of life of affected individuals. Early detection assumes an immense role in treatment, and this work demonstrates that resting-state electroencephalogram (EEG) data can be used to reveal potential tendencies of executive dysfunction at an early stage. An improved machine learning (ML) algorithm was successfully used in combination with deconvolution of EEG bandwidths and the results of a neuropsychological test - the Trail Making Test (TMT) - based on a finely graded equidistant electroencephalographic subband spectrum to develop and evaluate a classification model for identifying signs of executive dysfunction. The machine learning algorithm used achieved an accuracy of 75.00%, and to the best of my knowledge, this result set a new standard. Based on this preliminary study, a means of early diagnosis of potential schizophrenia patterns from resting-state EEG data may develop to aid intervention for early executive dysfunction, suggesting potential application in the medical field.

Keywords: Resting electroencephalogram (EEG); Random Forest; Executive Dysfunction; Schizophrenia; Trail Making Test

Introduction

In the health care environment, early and reliable detection of cognitive impairment or deterioration is a major challenge and opportunity, as quantitative assessment of cognitive function is a hugely important component of care for people with dysfunction due to, for example, traumatic brain injury [1]. Cognitive functions, such as reasoning, attention, memory, and language [2], enable humans to perform tasks, with executive functions acting at a higher level, primarily mediated by the prefrontal cortex [3–5]. Executive functions are controlled by brain systems and are relevant, for example, for prioritizing actions, coping with new situations, making decisions, assessing risks, and responding adaptively to the environment. Moreover, they are particularly responsible for planning, sequencing, or temporally structuring behavior and are thus indispensable in daily life [4,5]. Executive dysfunction occurs when these abilities are absent in an individual associated with the inability to perform instrumental activities of daily living, drastically reducing the quality of life [6,7]. To further the understanding of such abnormalities, and help affected individuals more effectively, neuropsychological tests, such as Wechsler Memory Scale (WAIS) [8], or Rey Auditory Verbal Learning Test (RAVLT) [9], are used in the medical setting to quantitatively assess executive function, which can efficiently detect functional disorders [10]. One of the most widespread and popular neuropsychological tests is the Trail Making Test, a two-part neuropsychological test used to analyse neurocognitive abilities and executive functions [11–15]. The origin of TMT is found as part of the Army Individual Test Battery (1944) developed by U.S. Army psychologists as a sensitive indicator of brain damage, which was incorporated into the Halstead Reitan Battery in 1958 [11–13,16,17]. TMT is usually performed in the medical domain to support the diagnosis of specific diseases like schizophrenia, Alzheimer's and Parkinson's diseases [18,19]. Especially in schizophrenia, cognitive impairment is one of the most common neurocognitive abnormalities, with deficits occurring in cognitive domains such as general intelligence, attention, working memory, verbal learning and especially the executive functions [10,20–23]. Impairments in executive functions are considered a primary deficit of schizophrenia, making it a core feature that occurs early in the course of the illness and is associated with refractory negative symptoms, such as aversion, perseveration, and incoherent behavior, making it significant for early diagnosis [24–26]. Accurate and early diagnosis is of utmost importance to target schizophrenia and increases the effectiveness of treatment. However, this is extremely problematic, as the complexity of schizophrenia makes a definitive diagnosis difficult, partly because the diagnosis is usually made using diagnostic criteria from the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), whereby patients are asked a series of questions to obtain relevant information [27,28]. Thus, the diagnosis of schizophrenia is made clinically by examining the mental state and based on the history, which makes the entire diagnosis time-consuming, burdensome, error-prone, and biased [29]. Also, there are no precise diagnostic tests or biomarkers available, making it necessary to obtain objective and quantitative data, such as using electrophysiological techniques like electroencephalography [27,30].

EEG data can be a tremendous support in the diagnosis, as they make it possible to recognize specific patterns in a person's ongoing brain activity and make these patterns available for processing [17,31]. The human brain interacts with all organs and coordinates the body´s functions, as well as being the center of senses, emotions, intelligence, and memory, and therefore can reveal an immense amount of information [32]. The detection of executive dysfunctions can play an enormous role in the early diagnosis of schizophrenia, which can be addressed even more efficiently using resting EEG data and the TMT scores under evaluable conditions [11–15]. EEG as a non-invasive technique that measures the electrical activity generated by the triggering of brain neurons can be advantageous because it requires minimal patient cooperation and does not depend on the motor or verbal responses, thus patients cannot hide possible symptoms [32,33]. Specifically, resting EEG data used in this study are considered a sensitive measure for discriminating between clinical disorders as the brain follows replicable norms at rest, defining the functionally appropriate perceptual-cognitive repertoire available [34,35]. Deviations from these norms are associated with dysfunction and specific changes, making abnormalities in resting EEG indicative of disruptions in neural interactions that have been shown to be reliable over time [34–36]. Typically, the amount of information in EEG signals is large, making human processing impossible, and thus putting machine learning (ML) in the foreground [37]. Progress in ML has made it possible to classify the data accurately, resulting in optimal processing of EEG data to directly identify the most relevant diagnostic variables and estimate their relative importance in the classification of cognitive impairments, which may improve diagnostic efficiency [19,37]. Explicitly, the identification and assessment of executive dysfunction can be supported by the combination of resting EEG, TMT scores, and machine learning, which can be of tremendous importance for neurological disorders in the medical domain [37].

The approach of using neuropsychological tests to interpret executive dysfunction is widely used in the literature and has been explored in other research, particularly the disorder´s impact on patient outcome and impairment, including in the context of schizophrenic patients. For example, Brazo et al. [38] found a significant deterioration in outcomes due to schizophrenia on the B-A Index, also known as the difference score. In addition, it was confirmed that schizophrenic patients with negative symptoms have severe executive dysfunction, which was reflected in the TMT results. Furthermore, it was found that cognitive impairment in schizophrenia is largely independent of general intelligence [38]. The B-A Index is a valid way to consider both parts of the test and thus obtain a wider range of information. Because of this, the difference score proves useful for this work, which is underscored by other work that has placed the index in context with cognitive functions [39,40]. In contrast, Heinrichs and Zakzanis [41] reported a significant decline in Part-B, although the B-A index was not yet so popular at the time. Li et al. [21] also examined the behavior of schizophrenics and healthy subjects and found that schizophrenia worsens scores on visual attention and graphomotor speed, which can be attributed to impaired executive functions. This was also supported by the work of Schuepbach et al. [10], who noted significant deterioration in TMT-A and TMT-B and highlighted the pathophysiological importance of cognitive and executive function in schizophrenia. In addition, deficits in executive functions were associated with changes in mean cerebral blood flow velocity (MFV) [10]. Woelwer and Gabel [4] also investigated the influence of executive dysfunction in schizophrenics on TMT scores, showing as results that the poorer performance during both parts of the TMT was due to the longer planning period with a higher number of search or planning fixations outside the cursor area, showing a multifactorial phenomenon. This is because planning is defined as an executive skill and relies on many other cognitive components such as attention, perception and memory [4]. In addition, there are isolated studies that have used TMT with EEG data to examine executive function and schizophrenia, such as Gomez-Pilar et al. [42] and Lee et al. [43], each of which discovered worsened performance due to the disease. Based on the literature, executive dysfunction results in a worse TMT score, whether in TMT-A or TMT-B, making the difference score a valid basis because both parts of the TMT are included, and a wide range of cognitive abilities are addressed. Subjects with a high difference score thus show patterns that resemble an executive dysfunction, which can be reconciled in terms of schizophrenia. Based on the knowledge of the other studies, the healthy individuals in the LEMON dataset can be assigned to two classes, depending on the result in the TMT.

Using the neuropsychological test TMT with linking of EEG data with an algorithm of machine learning, this work will classify an approach for possible propensities of executive dysfunctions in subjects, which could be used as a basis for possible early diagnoses of schizophrenia. To the best of our knowledge, such an approach does not exist in the literature, so only similar work is considered. Vacca et al. [44] used ML to find patterns in the data, through various neuropsychological tests, to address the diagnosis of schizophrenia, with the particularity that TMT was also used as an indicator and basis of assessment for executive functions. SVM and a neural network proved to be the best with an accuracy of 87.8% and 84.8% respectively, with executive functions placed as one of the 3 most important features for classification. The dataset used was from the neuroscience group, which included 86 schizophrenics and 115 healthy individuals. Another work, dealing with executive functions and schizophrenia using neuropsychological tests, is from Shen et al. [45]. In their work, attention deficits in schizophrenia patients were classified with 90.70% accuracy using a support vector machine that allows automated discrimination between healthy and schizophrenic individuals, indicating deficits in several cognitive functions, including significant executive function [45]. Shim et al. [28], on the other hand, did not use neuropsychological tests, but used EEG data, which showed an accuracy of 88.24% and revealed the reduced cognitive functions in schizophrenia patients compared to healthy controls. Again, healthy, and schizophrenic subjects were used, with the EEG data being most effective mainly in the frontal area (AF4, F1, Fz, F2, F3, F8, FC6, FT8). It can be inferred that the EEG patterns of individuals with executive dysfunction, which includes schizophrenic individuals, are significantly different from those of healthy individuals, allowing for a clear classification. This is also possible with resting EEG data, which was also demonstrated in the work of, for example, Kam et al. [34] or Andreou et al. [46], where the respective resting EEG data are used as a sensitive indicator of increased risk for mental illness in relation to schizophrenia, which is primarily executive dysfunction.

Based on the literature presented, the importance of ML-based methods in medicine, and the described efficiency of neuropsychological tests for interpreting executive dysfunction, as well as linking EEG data with ML, the possibility of a novel approach for classifying possible tendencies toward executive dysfunction in subjects was identified, which could be used as a basis for a possible early diagnosis of schizophrenia and is expected to expand research in this area. Building on this, the aim of this work was to develop a machine algorithm that could classify subjects with tendencies toward executive dysfunction and subjects without signs of executive dysfunction from nonmanipulable resting EEG data in combination with TMT results, providing a potential means for early diagnosis of schizophrenia patterns.

Research Methodology

This work was developed according to the methodology of the Design Science research approach of [47], which aims to improve problem-solving capabilities by creating innovative artifacts, which in this work argues for the machine learning algorithm according to developed guidelines. The methodology used is shown in Figure 1.

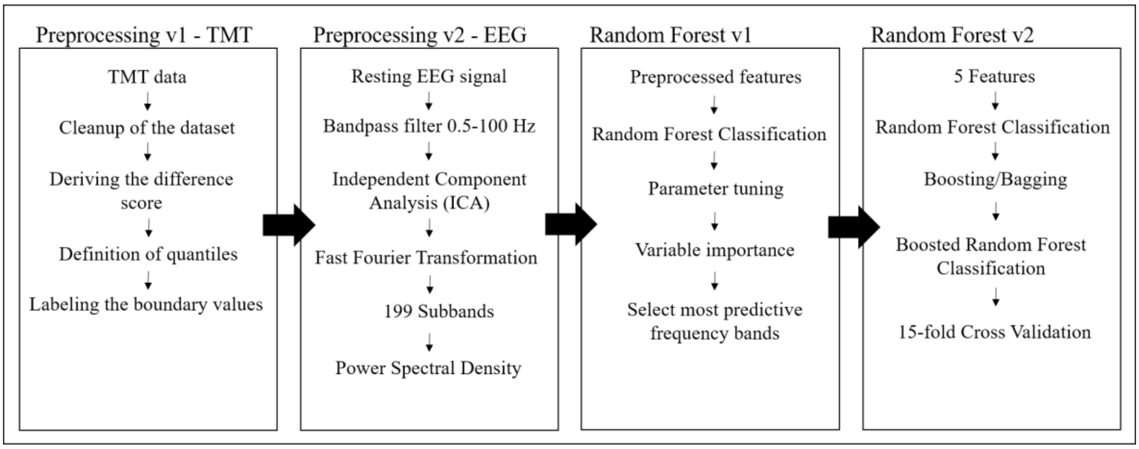

Figure 1. Overview of the methodology

Dataset

For this work, the publicly available mind-brain-body dataset called LEMON [48] was used, which was composed of 227 healthy participants. Two groups were available – a younger group (n=153, 25.1±3.1 years, domain 20-35 years, 45 women) and an older group (n=74, 67.6±4.7 years, domain 59-77 years, 37 women). 62-channel resting EEG recordings were collected from each participant, with electrodes – 61 scalp electrodes with an additional 1 VEOG electrode – attached according to the 10-10 Extended Localization System, all with reference to FCz. Data was collected at a sampling rate of 2,500 Hz, which was down sampled to 250 Hz in this work for better processing. The LEMON dataset was chosen because of its ability to comprehensively correlate cognitive and emotional features with physiological features of the brain. Even if the test data are from healthy individuals, the results can be used in clinical research since the resting EEG data in combination with the TMT results can reveal the first signs of disease.

Trail Making Test (TMT)

The Trail Making Test (TMT) is a two-part neuropsychological test that provides a means to analyse neurocognitive abilities and test for normative characteristics [11–15]. The test consists of two parts, an A part, and a B part, and both parts must be completed as quickly and accurately as possible [11, 12, 49]. In the A section, the respondent's task is to connect 25 randomly selected numbers in ascending order (1-2-3-4-...) [16, 50]. In the B-part, on the other hand, letters are present in addition to numbers and must be connected in alternating ascending order (1-A-2-B-3- C-...) [11–15]. The numbers are in an interval of 1-13, the letters from A-M [11]. Unlike part A, the individual numbers and letters can be arranged in a semi-random fixed order, so that overlapping lines are prevented in advance [16]. Furthermore, to ensure better connectivity, all numbers and letters are embedded in circles. The score of a test person is then finally determined by the time it took him/her to draw a line from the starting point to the end point [1]. The most important variable is the total time to complete Parts A and B, in this work looking at the B-A difference as an index of the degree of impairment caused by the additional flexibility component of Part B [16]. The TMT is considered flexible in the ranges of values because cutoff scores and stare limits to be established as indicators of disease have rarely been clinically enforced due to lack of specificity [16]. Therefore, raw time scores in the range of observations are considered informative for interpreting and tracking changes in the level of impairment and may vary by subject group, creating clusters that should provide insight into signs of disease [16].

Novel Machine Learning Approach

This novel algorithm for machine learning follows the approach that finer grained frequency bands can be used to achieve higher information content, thereby improving classification performance, and increasing information density [51]. Therefore, this approach is based on the fine-grained EEG spectra proposed by Buettner et al. [51], in which five standard EEG bands are replaced by a finely graded equidistant 99-band EEG spectrum. This has already been used with great success in the machine classification of other diseases such as epilepsy [52] or alcoholism [53] and is thus also a possible option for executive disorders.

The final classification in this work was done with the Random Forest algorithm presented by Breiman [54], which is an ensemble learning method with a combination of many decision trees, finally extended with AdaBoost. The algorithm was chosen because it has already been used successfully in the context of other diseases and achieved very good results with EEG data [52,53,55]. In addition, Random Forest is a way to train datasets efficiently and effectively, as trees make their decisions independently and thus allow parallel processing [54,56]. This makes the Random Forest a way to solve ML problems, combining and aggregating independent results to make a final decision based on consensus. Ensemble Learning is thus an effective way to optimize generalization, predictive performance, and robustness through a combined model [54,57]. In addition, the most predictive features of Random Forest were evaluated to further improve classification results.

Data Preprocessing and Machine Learning Model

Preprocessing of the dataset included an initial cleanup of subjects who, during the TMT, be it TMT-A or TMT-B, showed abnormalities in the procedure, such as a delayed start, not understanding the test, or repeating the test. Subsequently, missing values, which for example occurred during TMT-A, were replaced by average values from the remaining values. This is a valid strategy also known as Mean Imputation (MI) [58]. Consequently, additional data were added as the four direct results allow for the derivation of further results that better describe the cognitive skills required to perform the test. The direct outcomes are the respective times required to complete tests A and B and their errors in linking the results. Over time, the individual direct scores have given rise to further evaluation possibilities: the difference score (B-A), which is intended to remove the speed component from the test evaluation. The ratio score (B/A), which provides an indicator of the executive control function. The proportion score (B-A/A), which is a sensitive index of prefrontal cortex function, as well as the sum score (A+B) and the multiplication score (A×B/100) [12,17,59]. The derived scores were added to the dataset to provide further information about the subjects' results.Quantiles were used to define boundary ranges, each consisting of the upper 25% and the lower 25%, with negative difference score values removed beforehand to eliminate bias, resulting in a balanced dataset for the machine learning approach. Hereby, the test persons were divided according to their difference scores, so that a difference score > 42 is assigned to label 1, thus the low performers, and consequently a difference score < 20 to label 0, thus the high performers. In this way, it was ensured that the individual brain activities are as different as possible based on the difference score and a clear classification can be developed effectively. Thus, label 1 was defined as "slight signs of executive dysfunction" and label 0 as "no signs of executive dysfunction" in the context of TMT. Subsequently, the EEGs of each subject were linked to the data from the preprocessed dataset, which were resting EEG data acquired after the TMT was performed. During EEG data acquisition, subjects were identified who are susceptible to disturbing factors, also known as artifacts, such as muscle activity, eye movements, blinking and heartbeat. On this basis, the ICA algorithm was implemented, which works on EEG data to remove the corresponding artifacts [55,60]. The ICA-algorithm is relevant because EEG reflects many thousands of brain processes simultaneously in certain frequency bands and the corresponding frequency bandwidth [61]. With the ICA-algorithm, the disturbing factors can be removed, but only if the following assumptions are fulfilled: 1. The mixed medium is linear, and the propagation delays are negligible. 2. The time histories of the sources are independent. 3. The number of sources is equal to the number of sensors. For the application of ICA on the resting EEG data, the first two assumptions are fulfilled, since the recording is linear and instantaneous, and the sources of muscle activity, eye movements, blinking, and heartbeat are not time-dependent. Only the exact amount of statistically independent brain signals is unknown, making the third assumption questionable, which nevertheless has not affected the good results in this work with the ICA algorithm. For further processing of the EEG signals cleaned by ICA, the EEG signal is transformed into frequency signal using Fourier transformation. The EEG signals used are first primarily decomposed into sinusoidal oscillations with a known wavelength, whereby each wavelength is then checked for agreement with the EEG signal using correlation analyses. This results in a power spectrum, whereby an estimation about the distribution of the frequencies of the EEG signal is possible [62]. The classification of the frequency bands is based on the division into alpha, beta, theta, delta, and gamma bands, as shown in Table 1, which allows the findings of the study to be clearly assigned.

Table 1. Standard EEG bandwidths

Frequency band	Frequency range in Hz	Characterization
Delta	0.5 – 3.5 Hz	Sleep
Theta	3.5 – 7.5 Hz	Sleep & dream
Alpha	7.5 – 12.5 Hz	Relaxed awake, closed eyes
Beta	12.5 – 30 Hz	Inner restlessness, stress concentration
Gamma	>30 Hz	Extreme concentration

To cover the entire range and include all possible relevant information, a spectrum from 0.5 Hz to 100 Hz was analysed, allowing detection of abnormalities in the upper gamma frequencies (> 30 Hz), which is possible in executive dysfunctions associated with schizophrenia. The bands were unfolded in steps of 0.5 Hz, which demonstrably increases the information content of the finer frequency bands compared to the wide bands used in a classical division into alpha, beta, theta, delta and gamma [51]. For the machine learning approach, the Random Forest presented by Breiman [54] was used. This was chosen because it has performed very well in other work with EEG data and diseases, including schizophrenia, which was expected in this work [63,64]. Nevertheless, other classifiers were considered, such as the Support Vector Machine (SVM) [65], the Multi-Layer Perceptron (MLP) [66] and the k-nearest-neighbor classifier (KNN) [67], so that comparisons can be made rather than just relying on one algorithm. None of them could outperform the results of the Random Forest, so based on the performance, better interpretability, and analysis capabilities, the decision was made in favor of the Random Forest. The resulting 72 subjects were split into training and test data to train the algorithm and then test it on unseen data. For this purpose, the entire dataset was divided in a ratio of 90 (64 individuals) to 10 (8 individuals) to provide sufficient training. To ensure better machine processing, features were first normalized and then scaled using MinMaxScaler to preprocess all features to an interval of [0,1], further reducing potential bias. The Random Forest was examined with the methods GridSearch and RandomSearch to determine the best possible parameters that were used in the first instance for feature selection [68]. When considering the most important characteristics for the algorithm, it was found that the characteristics 12 Hz, 3 Hz, 11 Hz, 30 Hz and 29 Hz are most predictive for the classification, in descending order, and only these are considered for the further steps to further improve the result. A more detailed look at the 10 most predictive features and their significance can be found in Figure 2, where features with a significance value > 0.02 are considered for further process.

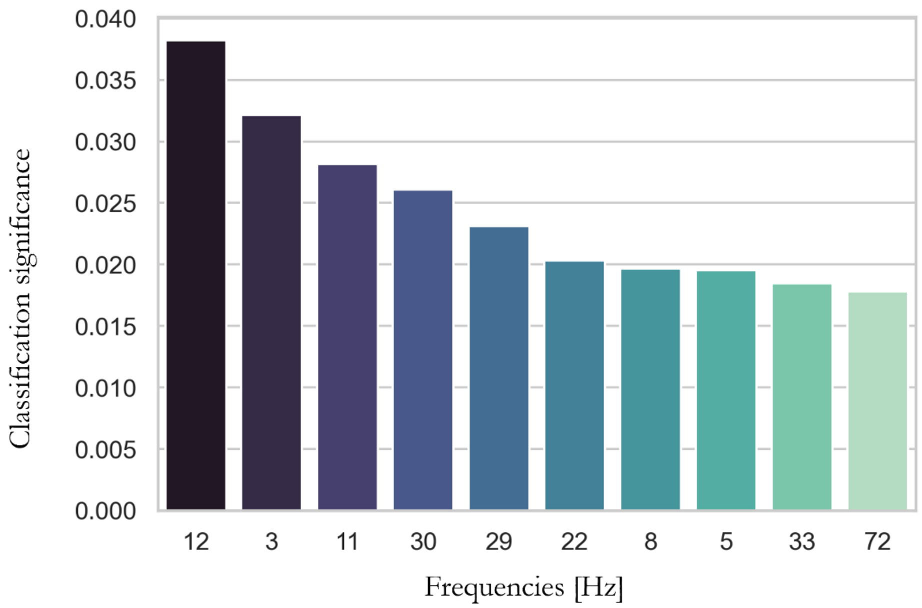

Figure 2. Detailed feature importance's

After isolating the most important features, the classifier was extended by various ensemble learning algorithms for boosting and bagging to further improve the accuracy of the model and to eliminate possible weaknesses. All algorithms were selected based on the different approaches and good results in other work. Namely, the gradient boosting algorithm [69], the bagging algorithm [70], the AdaBoost classifier [71], as well as more recent approaches like the XGBoost [72], and CatBoost [73]. The individual results after the validation of the results of the respective approaches are shown in Table 2, whereby the extended form of boosting – adaptive boosting (AdaBoost) – ultimately proved to be the most effective variant. AdaBoost, which was presented by Freund and Schapire [71], builds directly on the classical boosting algorithm, but extends it through an adaptive approach by incrementally building up an ensemble to adapt and improve training [71].

Table 2. Results of the advanced algorithms

Extending algorithm	Result of 15-fold cross validation (%)
Random Forest	70.31
Gradient Boosting	70.31
Bagging	64.06
AdaBoost	75.00
XGBoost	64.06
CatBoost	62.50

Validation Procedure

For evaluating the model in this paper, k-fold cross-validation with 15-fold CV [74] is used in addition to the hold-out procedure already described. The k-fold cross-validation subdivides the dataset used into k random subsets to compare each subset with the model and its prediction, thus identifying and validating performance and errors.

The results were recorded with a confusion matrix, recording the correct and incorrectly classified subjects, and is structured as follows: (i) True positive: The values belong to the upper border, which implies slight signs of executive dysfunctions and was correctly assigned by the model. (ii) False negative: The values belong to the upper border, which includes slight signs of executive dysfunctions and was incorrectly assigned to no signs. (iii) False positive: The values belonged to no signs of executive dysfunction and were incorrectly assigned to the slight signs. (iv) True negative: The values belonged to subjects with no signs of executive dysfunction and were correctly assigned by the model.

The following metrics were used associated to the performance indicators: the standard deviation (STD), as a measure of the variation or spread of values around the mean [75], the standard error (SE), which is defined as the standard error of the mean [76], and the coefficient of variation (CV), also known as relative standard deviation (RSD), which acts as a standardized measure of dispersion and to indicate precision [77]. To furthermore quantify performance indicators, the so-called "one-standard error rule" was used, where the standard deviation of the prediction error estimates is used, defining the standard error of the mean estimate [78,79].

Results

The AdaBoost extended Random Forest was able to show an overall accuracy of 75.00%, with the number of trees for growth set at 1,000 (ntree), which gives the best possible result. Accuracy indicates how often the algorithm correctly classifies a data point, which defines the number of correctly predicted data points over 15-folds among all data points. The algorithm predicted the high-performers with a true-negative rate of 75.76% and negative predicted value of 75.76%, whereas the low-performers had a true-positive rate of 74.19% and a positive predicted value of 74.19%. The following confusion matrix in Table 3 shows the statistical performance indicators representing the mean result of the 15-fold cross-validation. In addition, Table 4 lists additional performance indicators that provide further insight into the performance of the classifier:

Table 3. Confusion Matrix: Mean result of the 15-fold cross-validation

		Reference	
		Slight signs of executive dysfunction	No signs of executive dysfunction
Prediction	Slight signs of executive dysfunction	23	8
	No signs of executive dysfunction	8	25

Table 4. Performance indicators

Performance indicator	Value	STD	SE	CV
Overall Accuracy, %	75.00	0.25	0.07	0.32
Balanced Accuracy, %	74.97	0.25	0.07	0.32
Sensititvity (true positive rate), %	74.19	0.36	0.10	-
Specificity (true negative rate), %	75.76	0.35	0.09	-
Positive Predicitve Value, %	74.19	0.34	0.09	-
Negative Predictive Value, %	75.76	0.34	0.09	-
Prevalence, %	48.44	-	-	-
F1-Score, %	75.00	0.31	0.08	-

STD = standard deviation; SE = standard error; CV = coefficient of variation

The additional performance indicators were chosen to further illustrate the results and place them in a broader context. The standard deviation indicates how close the results are to the mean of the total foldings, where an STD of 25% in accuracy occurred. The SE is 7%, which, like the STD, could be due to the relatively small data set, but provides benchmarks for an initial study that should be improved in the future. In addition, coefficient of variation is also relatively high, indicating scatter in the results, which is due to two very weak folds within the results at 25% each. These should have included very similar patterns, which can occur with healthy subjects and also reduces the overall accuracy. Nevertheless, the values are good cornerstones that provide insight into the behavior of the algorithm and bring transparency to this work. The prevalence is 48.44%, reflecting a balanced data set in terms of signs of schizophrenia patterns and no signs, which is valid for this study by the chosen methodology, but would hardly be conceivable in a real clinical scenario. This also compromises the results in accuracy and balanced accuracy, highlighting the 75% accuracy as a good first result in this field of research. Also, the F1 score of 75%, which is calculated from precision and recall and defined as the harmonic mean of these two, represents a good first value for future work in this area.

Discussion

Identifying executive dysfunction from resting EEG data provides an efficient way to detect potential disease early and without patient interaction based on brain activity. Based on the results of the presented algorithm, conclusions can be drawn about the main frequency sub-bands focusing on the results with executive dysfunction, as well as in the context of schizophrenia, as executive dysfunction plays a significant role in the early stage and thereby in the early diagnosis of schizophrenia, with overlapping results further demonstrating this.

The detected frequency band 2.5-3 Hz belongs to the delta range, whereby the division of the ranges was made according to Table 1. Increased delta in combination with decreased alpha, which was revealed in this work, may indicate psychosis reflecting an inappropriate state of arousal [80]. In addition, delta/alpha frequency activity can be used to neurophysiologically isolate psychotic disorders to reveal patterns of executive dysfunction that may be indicative of schizophrenia, which supports this work [80]. In the work of Knott et al. [81], increased performance in the delta bands and increased performance in the theta bands was also assessed, which was not the case for the results in this work, which may well be due to the complexity of schizophrenic traits. Delta enhancement was recorded maximally in frontal and temporal regions, and theta enhancement was generalized. Also an increased delta activity was reported by Mukundan [82], whereas theta activities were reduced, which is consistent with the findings of this work. In addition, parts of beta activity were increased, but only in frontal regions, while theta activity was reduced in temporal areas, which is only suspected in this work and should be investigated in more detail in future work and gives room for new approaches. The 10.5-11 Hz and 11.5-12 Hz sub-bands are assigned to the alpha domain, which may show spikes in neurological and psychiatric disorders. This may reflect executive dysfunction and has been identified as a possible pattern for schizophrenia [83]. In addition, performance abnormalities in the low-frequency and alpha bands are prevalent in schizophrenia, possibly indicating dysfunction of the patient's thalamus and frontal lobe related to executive dysfunction [84]. The other important sub-bands discovered are 28.5-29 Hz and 29.5-30 Hz, i.e., in the uppermost beta domain and bordering on the lower gamma domain. This occurrence is consistent with the fundamental findings of Ray and Cole [85], who classified the EEG beta as a useful measure of appropriate cognitive and emotional processes that directly target executive functions, which is consistent with the TMT, being directly targeted to cognitive processes. Beta waves, moreover, have the property of showing larger changes under external stimulation, which can better represent the differences between patients with different degrees of illness when visual emotional stimulation is applied, here interesting for schizophrenia patients with different stages of executive dysfunction [86]. Moreover, Nikulin et al. [87] found a cross-frequency correlation between oscillations involving alpha and beta, concerning neurophysiological processes of neuronal dynamics in both frequency ranges that can distinguish patients with executive dysfunction from healthy subjects, which is also conceivable for schizophrenia patients.

This distribution of sub-bands can be attributed to the complexity of executive dysfunction with respect to schizophrenia; similarly, broad distributions of the major sub-bands can be found, for example, in [55] or [88]. Nevertheless, it should be highlighted in the presented distribution that the bands in the domains 10.5-11 Hz and 11.5-12 Hz, as well as 28.5-29 Hz and 29.5-30 Hz, are directly adjacent, according to the chosen division. This opens the possibility to consider both 10.5-12 Hz, and 28.5-30 Hz, defining divisions of potential indicators of signs of executive dysfunction that can bring information about an early phase of schizophrenia. It should be additionally emphasized that the subjects labeled and classified with mild signs of executive dysfunction were assigned to this labeling based only on the results of the TMT difference score and their corresponding resting EEG data. The dataset is based on healthy subjects, but the procedure shown still allows to identify and classify signs of executive dysfunction, which was demonstrated with a good result.

A comparison of the obtained values from Table 4 with similar works should be put in relation, since this work is the first with the presented approach and should be the cornerstone for upcoming ones. The accuracy of 75% still has potential for improvement, since an accurate diagnosis is a top priority in the medical field, but this should be improved by samples with schizophrenia in the first place, which should make the patterns for the random forest more unambiguous. Especially in the medical field, the use of a random forest is conceivable, as it can provide relatively fast as well as accurate results after initializing the forest and offers simple and efficient processing of thousands of input variables [89]. In addition, the number of samples used is small, which is sufficient for a first study, although the algorithm can probably provide even better results with more samples, which is not always guaranteed in the medical field, which is why a transfer learning approach would also be conceivable [90]. In addition, a prevalence of 48.44% from Table 4 is present in the dataset, which does not reflect a real scenario in the population, as the proportion of schizophrenia sufferers is significantly smaller than that of non-schizophrenia sufferers. This goes along with the dataset used, whereby the number, health status and distribution of subjects negatively affected the accuracy of the algorithm, but this will be eliminated in upcoming work and should lead to potentially better results.

Limitations

The limitations of this work are that the results of this study and the algorithm have not yet been tested in a clinical setting and therefore have not yet been tested in practice. In addition, the internal validity of the classifier is very high due to the operation of k-fold cross-validation, but the external validity of the results is another limitation. Also, the EEG dataset used can be seen as a limitation. It excludes subjects with a history of executive dysfunction from the study. Only healthy subjects were included in [48]'s study, which subsequent studies will compensate for in the future.

Future Work

Since an efficient approach has been found to classify the individual patterns in healthy individuals, it is conceivable to apply this approach to datasets with diseased individuals. Based on this, this approach can be considered as a preliminary study and it is intended to apply the algorithm to schizophrenic subjects to evaluate the good results regarding the classification of executive dysfunction, which is a significant indicator in the early stage of schizophrenia, for the early diagnosis of schizophrenia, further advancing the progress of machine learning in the medical domain. Primarily using healthy subjects to conduct a preliminary study is a valid strategy, which is also shown, for example, in the work of Alchalabi et al. [37] with success. The possibility of looking at individual brain regions separately should also be considered in the future, as results from other work have shown. It is conceivable that isolated consideration of, for example, central brain regions will provide further insights that also support early diagnosis of schizophrenia, as will the explicit consideration of the domains 10.5-12 Hz, and 28.5- 30 Hz, which were revealed to be significant in this study. Furthermore, subjects were assigned based on the results of the TMT test, which revealed significant differences in resting-state EEG data. Additional neuropsychological tests that take into account information about executive functions from other observational vectors would allow further objective and diagnostic categorization of subjects to include additional factors for analysis. An example would be the Wisconsin Card Sorting Test (WCST), which has produced significant results in executive dysfunction and schizophrenic subjects [91]. In addition, the identified EEG resting state sub-bands that distinguished healthy people from people with signs of executive dysfunction will be applied in an adapted deep learning approach using convolutional neural networks [92]. These approaches can be used to improve the performance of the classifier and further investigate the presented concept. By providing an objective, physiologybased assessment using resting-state EEG, this work contributes to health information systems research and technology acceptance of a new IS artifact [93,94].

Conclusion

An efficient ML algorithm was successfully developed to classifying signs of executive dysfunction using resting state EEG data. The boosted random forest achieved an overall accuracy of 75.00%, which is the first of its kind to set new standards and achieve a first prediction gain in this field. In addition, the five most predictive resting EEG sub-bands that significantly distinguish healthy individuals from those with signs of executive dysfunction were identified and placed in a detailed scientific context. The results of this study support existing knowledge from the literature on executive dysfunction associated with schizophrenia. Furthermore, new insights could be presented through the presented distribution of frequency bands and their significance. Through the findings on executive dysfunction and its relevance to schizophrenia, this work represents a successful preliminary study that can be applied to schizophrenia patients in the future through non-invasive and objective neurophysiological measurements for a future approach to possible early detection.

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